Asset Returns and the Listing Choice of Firms

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Abstract

We propose a mechanism that relates asset returns to the firm's optimal listing choice. The crucial element in our framework is not a difference in the structure or rules of the alternative markets, but a difference in the return patterns of the securities that are traded on these markets. We use a simple trading model with asymmetric information to show that a stock would be more liquid when it is listed on a market with "similar" securities, or securities with correlated payoff patterns. We empirically examine the implications of our model using NYSE and Nasdaq securities, and document that the return patterns of stocks listed on the NYSE indeed look different from the return patterns of Nasdaq stocks. Stocks that are eligible to list on another market but do not switch have return patterns that are similar to other securities on their own market and different from securities listed on the other market. We show that the return patterns of stocks that switch markets change in the two years prior to the move in the direction of being more similar to the stocks on the new market. Our results are consistent with the notion that managers choose the market on which to list to maximize the liquidity of their stocks.

Asset Returns and the Listing Choice of Firms

One of the major decisions made by managers of firms is where to list their stocks. Together with decisions on financing and payout policy, the listing choice affects investors and has the potential to impact the value of the firm. The literature on the listing choice suggests a couple of ways by which optimal listing can benefit investors. For example, listing on the market that is more appropriate for a firm can improve liquidity.[1] Investors value the lower cost of transacting in the stock and therefore such an improvement would increase the value of the firm (Amihud and Mendelson, 1986). Listing on a more appropriate market can also increase the visibility of a firm.[2] More visibility attracts a larger investor base and can therefore result in a higher firm value (Merton, 1987).

In the U.S., researchers have attempted to analyze the determinants of managers' optimal choice in the context of two dominant markets, the New York Stock Exchange (NYSE) and the Nasdaq National Market. Because there are differences in the structures, rules, and listing requirements of these two markets, much of the research has focused on identifying the structural element or the rule that either makes one market superior to the other or explains the reasoning behind the decisions of some firms to list on Nasdaq and others on the NYSE.

For example, Heidle and Huang (2002) and Lipson (2002) observe that the NYSE is a centralized floor-auction market while the Nasdaq is a fragmented screen-based market with multiple dealers and alternative trading systems. If some investors have private information and they can better hide in a fragmented screen-based market, moving from Nasdaq to the NYSE would benefit investors by reducing the extent of adverse selection. Foucault and Parlour (2003) note that different markets may charge different listing fees, a situation that characterizes the NYSE and Nasdaq. They provide a model where firms self-select to the

[1] See Grammatikos and Papaioannou (1986), Sanger and McConnell (1986), Edelman and Baker (1990), Sanger and Peterson (1990), Cowan, Carter, Dark, and Singh (1992), Christie and Huang (1994), Kadlec and McConnell (1994), Elyasiani, Hauser, and Lauterbach (2000), Kalay and Portniaguina (2001), and Bessembinder and Rath (2002).

[2] See Kadlec and McConnell (1994), Aggarwal and Angel (1997), and Baker, Powell, and Weaver (1999a, 1999b).

most appropriate market as a tradeoff exists between listing fees and transaction costs. Wan (2001) argues that the different market structures give rise to different volume figures on the NYSE and Nasdaq, and that SEC rules restricting the trading of insiders are therefore less binding on Nasdaq. His argument implies that incentives of insiders that are not shared by outside shareholders may affect the listing choice.[3] Cowan, Carter, Dark, and Singh (1992) suggest that NYSE rules discouraging unequal voting rights of multiple share classes may also influence the decision of managers on where to list.[4]

In this paper we propose a new determinant of the listing decision. We abstract from the particular features of U.S. markets and instead put forward a mechanism that relates the firm's asset returns to the optimal listing choice. The crucial element in our framework is not a difference in the structure or rules of the markets, but rather a difference in the return patterns of the securities that are traded on these markets.

We begin by developing a simple trading model where multiple securities are traded in one of two markets and there is information asymmetry among investors. We show that a stock is more liquid when it is listed on a market with "similar" securities, or other securities with correlated payoff patterns. The driving force behind the result is that market makers can extract useful information about the value of the stock from the order flows of other securities in the market. Therefore, trades have smaller price impacts (or lower adverse selection costs) reflecting greater confidence market makers have in the prices they set. If adverse selection and other impediments to liquidity are priced (e.g., Amihud and Mendelson, 1986; Easley and O'Hara, 2004), our model suggests that a manager who maximizes shareholder value would want to list his stock on a market with similar securities.

This insight can explain why managers of firms often cite their desire to be on a market with similar firms as a motive for choosing to list on a particular market. For example, the Chairman and CEO of Allied Capital commented on their move from Nasdaq to the NYSE

[3]See also the models of Huddart, Hughes, and Brunnermeier (1999) and Chemmanur and Fulghieri (2003) that demonstrate how insiders' listing decisions can be affected by public disclosure requirements.

[4]See also Aggarwal and Angel (1997), Bessembinder (2000), Corwin and Harris (2001), and Jain and Kim (2004).

saying "There aren't a lot of dividend-paying stocks on Nasdaq, and, as a dividend payer, we really think our stock is better suited to the NYSE." President and CFO of Aeroflex was quoted on their move from the NYSE to Nasdaq saying "We believe listing on Nasdaq will help position Aeroflex among its peer group of other high technology companies." The CFO of CARBO Ceramics noted on the move of his firm from Nasdaq to the NYSE "Although the Nasdaq National Market has been extremely helpful to us since our initial public offering in 1996, we believe that our move to the New York Stock Exchange is consistent with the NYSE listing of the majority of publicly-traded companies in the oilfield services industry."[5]

These quotes suggest that while managers of firms may not be thinking explicitly in terms of the comovement of their stocks' returns with those of other firms, they probably have an intuitive notion of what constitutes a "similar" firm. Therefore, our model provides the rationale for why firms in the same industry, presumably having more commonality in their return patterns, tend to list on the same market. The quote about Allied Capital's move suggests, however, that industry membership may not always be the determining criterion. A mature firm in a certain industry may have more in common with a mature firm in another industry than with a start-up in its own industry. When a firm matures and its payoffs change to reflect more of the general conditions in the economy, it may be better off switching to a market with other mature firms. This seems to correspond to the path many firms take when listing for the first time on Nasdaq and then moving to the NYSE. Still, not all Nasdaq firms that are eligible to list on the NYSE switch markets.

We therefore proceed to empirically examine the implications of our model using NYSE and Nasdaq securities in 2001. There is more than one way in which we can define similarity in the return patterns of securities, and each definition suggests a different empirical methodology. The first definition we implement draws on an interpretation of the signals in our model as private information about common factors in returns (see also Subrahmanyam,

[5]The quotes are taken from: (i) "Allied Capital Corp. Moves to Bid Board" by Robyn Kurdek in the Venture Capital Journal, June 1, 2001, (ii) a press release by Aeroflex Incorporate, February 17, 2000, and (iii) "CARBO Ceramics Announces Completion of Public Offering and Move to the New York Stock Exchange" on the PR Newswire, May 19, 2000.

1991; Caballe and Krishnan, 1994). We therefore examine similarity in returns by looking at the loadings of securities on estimates of common factors from a principal component procedure. Our second definition does not associate private information in the model with common factors. Rather, the private signals contain information that is relevant to a subset of stocks, and better estimates of the sensitivities to the signals (that determine the optimal listing choice in our model) can be obtained by eliminating the market component in returns and examining correlations of return residuals.

Our first test provides a check on the basic assumption in the model that the two markets differ in terms of the return patterns of the stocks that are listed on them (or that stocks listed on the NYSE have different return patterns from those of Nasdaq stocks). We create four groups: (i) Nasdaq National Market stocks that are eligible to list on the NYSE, (ii) Nasdaq National Market securities that are not eligible to list on the NYSE, (iii) NYSE stocks that are eligible to list on Nasdaq, and (iv) NYSE securities that are not eligible to list on Nasdaq. We conduct a principal component analysis of 60 portfolios, 15 from each of the four groups, using daily returns in 2001. We find that Nasdaq securities load more heavily on the first principal component and that NYSE securities load more heavily on the second principal component, consistent with the basic assumption of our model.

When testing the model's predictions, we look both at firms that switch markets and at firms that are eligible to switch but stay. While managers of the switching firms make an "active" decision to move, managers of those remaining make "passive" decisions that impact the liquidity of their stocks. We start by examining the "passive" decisions of firms that are eligible to move but do not. Our model predicts that, if managers of firms seek to improve liquidity by their choice of listing, Nasdaq stocks that are eligible to list on the NYSE but do not move will load more on the same common factor as non-eligible Nasdaq securities and less on the common factor to which NYSE securities are more sensitive. A similar logic applies to NYSE stocks that are eligible to list on Nasdaq but do not move, and we would expect them to resemble other NYSE securities more than Nasdaq securities.

Our principal component analysis demonstrates that this is indeed the case: Nasdaq firms that are eligible to list on the NYSE but remain on Nasdaq have similar loadings to other Nasdaq firms, but very different loadings from those of NYSE firms. NYSE firms that are eligible to list on Nasdaq indeed look very similar to other NYSE firms but very different from Nasdaq firms. We then apply our second definition of similarity in return patterns by constructing estimates of the sensitivities to the signals using correlations of normalized residuals from market model regressions. Our model predicts that for eligible stocks, the sensitivity to the signal that affects securities in their own market should be greater than the sensitivity to the signal that affects securities in the other market. We find that this is indeed the case, and therefore the results using both definitions of similarity in return patterns support the notion that the "passive" decisions managers make by remaining listed on their markets are optimal with respect to liquidity.

We then examine the "active" choices made by managers of firms who move between Nasdaq and the NYSE in 2001. Looking at switching firms also demonstrates the robustness of our conclusions to an alternative hypothesis that listing on a market attracts market-specific liquidity trading and thus induces similarity in the return patterns of the listing firm and other firms traded on the same market. The empirical tests contrast our model with the alternative hypothesis by looking at the return patterns of firms that switch listings from one market to another before they switch. We find evidence of a change in the return patterns two years prior to the move to the new market, and that the return patterns of stocks that switch change in the direction of being more similar to the stocks listed on the new market. These results support the conclusion that managers make optimal listing decisions.

One contribution of our work is that it proposes a new determinant of the listing choice. We show how the listing venue affects liquidity through the learning process of market participants about private information in prices. We test the model (both the assumption and the implications) using various methodologies and find that managers seem to behave optimally in the sense of our model—as if they want to maximize the liquidity of their stocks.

When firms behave this way, the mechanism we propose as a determinant of the listing choice would perpetuate itself. In other words, when firms make active decisions to list on markets already populated by similar firms, the assumption of our model that the two markets differ in terms of the return patterns of the firms that are listed on them will continue to hold. As long as the assumption holds, the optimal listing choice will be to join the venue where similar firms are listed. Hence, this determinant of the listing choice seems robust to changes in the structures or rules of markets.

Another contribution of our approach is to propose a relation that goes from asset return patterns to the decisions of managers through an information-asymmetry-driven market microstructure trading model. Dow and Gorton (1997) and Subrahmanyam and Titman (2001) recently presented models where a manager can learn useful information from his firm's stock price. Our analysis suggests that certain managerial decisions would benefit from examining the firm's return pattern alongside the return patterns of other securities in the market. And while we find support for the optimal listing choices of NYSE and Nasdaq firms, the nature of our approach provides an intuition that is more general than the specifics of these two markets.

The rest of the paper proceeds as follows. We present the theoretical model and derive the implications for the relation between the listing choice and liquidity in Section 1. Section 2 is devoted to the empirical work: the sample construction, the tests on eligible and non-eligible securities, and the tests using switching firms. Section 4 is a conclusion.

I Theory

The purpose of this section is to develop a simple model that relates the listing choice to liquidity. We first describe the market prior to the listing of a new asset. We consider an economy with one risk-free asset and two risky assets (asset 1 and asset 2). Without loss of generality, we set the return on the risk-free asset to zero. Each risky asset is traded in a separate market organized as in Kyle (1985), where prices are set by competitive and risk-neutral market makers.[6] After each round of trading, there is a public release of information and the competitive market makers agree that the values of risky assets 1 and 2 have changed by the payoff innovations $\tilde{s}_1 + \tilde{\theta}_1$ and $\tilde{s}_2 + \tilde{\theta}_2$, respectively. We further assume that $\tilde{s}_1, \tilde{s}_2$ are standard normal random variables, independent of each other and independent of $\tilde{\theta}_1$ and $\tilde{\theta}_2$. The random variables $\tilde{\theta}_1$ and $\tilde{\theta}_2$ have zero means and can be correlated with each other.

We view each asset in the model as representing a group of similar assets traded on a single market. To simplify the exposition, we assume that assets listed on one market have a payoff component that does not exist in the payoffs of assets listed on the other market. Similar results can be obtained if asset payoffs in both markets are weighted averages of both $\tilde{s}_1$ and $\tilde{s}_2$, but the weight on $\tilde{s}_1$ is greater in one market and the weight on $\tilde{s}_2$ is greater in the other market. The primitive of our approach therefore is that similar assets (those with a common payoff component) are listed on the same market. We then investigate the implication of this assumption to the choice of a firm that considers where to list or whether to move from one market to another when the distribution of its payoffs changes.

The economy is populated by liquidity traders, informed traders, and two groups of market makers. We assume that the aggregate demand of the liquidity traders for each asset is a standard normal random variable that is independent of all other innovations in the market. There are two risk-neutral informed traders. The first one observes the realization of $\tilde{s}_1$, which is an unbiased signal of the payoff of asset 1. Similarly, the second informed trader observes the realization of $\tilde{s}_2$. As in Kyle (1985), anonymity of traders implies that market makers observe only aggregate net orders.

Since we posit two markets that are identical with respect to their structures and rules, we need to introduce some sort of segmentation in order to have a meaningful distinction between them. Therefore, we assume that market makers observe only the aggregate order flow that arrives in their own market before setting clearing prices. Benveniste, Marcus, and Wilhelm (1992) and Coval and Shumway (2001) claim that traders in one market have

[6] See also Baruch, Karolyi, and Lemmon (2003) who investigate international cross-listings in a multi-market model in the spirit of Kyle (1985).

access to valuable information that is not shared by traders in another market. Chowdhry and Nanda (1991) model a single asset that is traded on different exchanges. They also assume that market makers in a given exchange observe only the order flow that arrives to their exchange. This is the feature that distinguishes one market from another in their model, and similarly in our framework.[7] Note that the segmentation we consider is only at the time the order flow arrives in the market. After a trade has taken place, market makers in one market may observe prices set in the other market. Since we assume public release of information after each round of trading, the model allows for economy-wide reporting of last-trade prices.

We now introduce another risky asset, asset 3, that could potentially be listed on either market. The innovation of asset 3 is given by $a\tilde{s}_1+b\tilde{s}_2+\tilde{\theta}_3$, where a and b are scalars and $\tilde{\theta}_3$ is a zero mean random variable, independent of $\tilde{s}_1$ and $\tilde{s}_2$, but possibly correlated with $\tilde{\theta}_1$ and $\tilde{\theta}_2$. The liquidity demand for this asset is a standard normal random variable, independent of all other random variables. The scalars a and b are the sensitivities of asset 3's payoffs to the innovations $\tilde{s}_1$ and $\tilde{s}_2$. Say asset 3 is listed on market 1, where asset 1 is traded. Then, market makers price asset 3 based not only on its own aggregate demand but also on the demand they observe for the other asset listed on the same market. Similarly, if asset 3 is listed on market 2, market makers can observe the aggregate demands for both assets 2 and 3 when setting the price of asset 3.

Segmentation of markets and risk-neutrality of the informed traders imply that the trading strategies and price rules in one market are unaffected by the trading activity taking place in the other market. We can therefore study the outcome of each market separately, and we focus on the market where asset 3 is listed.

[7] Our empirical work in Section II uses NYSE and Nasdaq as the two markets. If, as in Benveniste, Marcus, and Wilhelm (1992), human interaction on the NYSE floor conveys information, Nasdaq market makers have no access to information that NYSE specialists observe. Linkages such as ITS (the Intermarket Trading System) do not alleviate this informational friction because only orders a market wishes to pass on to another market travel through ITS as opposed to the entire order flow. Also, conversations with practitioners suggest that many trading desks on Wall Street are organized such that traders in listed stocks sit together and traders in over-the-counter stocks sit together, facilitating better information sharing on stocks that are traded on the same market.

Consider first the case in which asset 3 is listed on market 1. We can write the value of the assets traded in market 1 using matrix notation as

$$\tilde{V} = \mu + F\tilde{S} + \tilde{\Theta},$$

where $\mu \in R^2$ is the value of the assets prior to the innovation, F is a matrix of scalars given by

$$F = \begin{pmatrix} 1 & 0 \\ a & b \end{pmatrix}, \tag{1}$$

$\tilde{S} = (\tilde{s}_1, \tilde{s}_2)$ is the vector of payoff-relevant signals of the informed traders, and $\tilde{\Theta} = (\tilde{\theta}_1, \tilde{\theta}_3)$. Let $\tilde{Z} \in R^2$ be the orders submitted by the liquidity traders to market 1. Let $X_1 \in R^2$ and $X_2 \in R^2$ be the orders submitted by the first and second informed traders, respectively. Note that each informed trader can submit orders for both assets 1 and 3. Let $\tilde{P} \in R^2$ be the clearing prices of the two assets, $X = X_1 + X_2$ be the aggregate demand of the informed traders, and $Y = X + Z$ be the net order flow submitted to the market.

An equilibrium is a price rule $P : R^2 \to R^2$ and strategies $X_1, X_2 \in R^2$ such that: (i) given the strategies, the price rule satisfies the condition $\tilde{P} = E[\tilde{V}|\tilde{Y}]$, and (ii) given the price rule, the i-th informed trader ($i = \{1, 2\}$) maximizes the expected profits $E[(\tilde{V} - \tilde{P})X_i|s_i]$.

Theorem 1. There exists a linear equilibrium in which (i) the price rule is given by $P(\tilde{Y}) = \mu + \Lambda\tilde{Y}$, where Λ is a 2×2 matrix of scalars, and (ii) aggregate informed trading can be written as $X = \beta S$, where β is a 2×2 matrix of scalars. The matrices Λ and β are the solutions to the system of equations (2) below satisfying the second order condition that $-(\Lambda^{\mathsf{T}} + \Lambda)$ is a negative semidefinite matrix:[8]

$$\begin{aligned} \beta &= (\Lambda + \Lambda^{\mathsf{T}})^{-1}F \\ \Lambda &= F\beta^{\mathsf{T}}(I + \beta\beta^{\mathsf{T}})^{-1} \end{aligned} \tag{2}$$

Proof of the theorem can be found in Appendix A. In equilibrium, the diagonal entries of the matrix Λ are the price impacts of market orders in asset 1 and asset 3. Let $\lambda_3(1)$ be

[8]Superscript T denotes the transpose operation and I denotes the identity matrix.

the price impact of market orders in asset 3 when it is listed on market 1 (i.e., the second row, second column entry of the matrix Λ). Similar to λ in the single-asset Kyle (1985) model, $\lambda_3(1)$ measures the liquidity of asset 3. Indeed, an uniformed trader who demands z of asset 3 expects to pay $z^2\lambda_3(1)$ for immediacy. It follows from the proof provided in Appendix A (see equation (6)) that

$$\lambda_3(1) = \frac{a^2 + |b|\,(1+|b|)}{2\sqrt{a^2 + (1+|b|)^2}}.$$

In order to compare liquidity when an asset is listed on one market versus the other, we need to find the price impact of market orders when asset 3 is listed on market 2. It is straightforward to show that a similar linear equilibrium exists in this case as well, where the price impact of market orders in asset 3 is given by[9]

$$\lambda_3(2) = \frac{b^2 + |a|\,(1+|a|)}{2\sqrt{b^2 + (1+|a|)^2}}$$

.

To determine whether liquidity is better when asset 3 is listed on market 1 or on market 2, we calculate the difference

$$\lambda_3(1)^2 - \lambda_3(2)^2 = \frac{b^4 - a^4 + 2(|b|^3 - |a|^3) + b^2 - a^2}{4\,(a^2 + (1+|b|)^2)\,(b^2 + (1+|a|)^2)} \tag{3}$$

The following proposition follows immediately:

Proposition 1. If $|a| > |b|$ then liquidity is better when asset 3 is listed on market 1, and if $|b| > |a|$ then liquidity is better when asset 3 is listed on market 2.

Proposition 1 states that if the magnitude of the sensitivity of asset 3 to $\tilde{s}_1$ (the payoff-relevant private information of the first informed trader) is greater than the magnitude of its sensitivity to $\tilde{s}_2$, then liquidity will be better if the asset is listed on market 1. Conversely, if the magnitude of the sensitivity of asset 3 to $\tilde{s}_1$ is smaller than its sensitivity to $\tilde{s}_2$, then liquidity will be better if the asset is listed on market 2

[9] The proof is analogous to the one of Theorem 1 and is therefore omitted for brevity.

What is the intuition behind this result? The key can be found in the off-diagonal terms of the matrix Λ that are specified in the proof of Theorem 1. They represent the market makers' inference from order flow of one asset that is relevant to the price of the other asset. In the model, if we assume that θ_1 and θ_3 are uncorrelated, a is the comovement of the payoffs of asset 1 and asset 3. Heuristically, the greater the magnitude of a, market makers can learn more about the payoffs of asset 3 by observing the order flow in asset 1.[10] As such, they do not need to change their beliefs (and hence the price) to the same extent in response to the order flow in asset 3, and therefore the price impact of market orders in asset 3, $\lambda_3(1)$, is smaller. In other words, the liquidity of asset 3 when listed on market 1 will be better than its liquidity when listed on market 2 if asset 3 comoves more with asset 1 than with asset 2. In a similar fashion, when asset 3 comoves more with asset 2 than with asset 1, or when $|b| > |a|$, liquidity will be better if asset 3 is listed on market 2.[11]

In fact, it is possible to show that not only does the liquidity of asset 3 changes depending on where it lists, but also the liquidity of the existing asset in the market on which asset 3 lists improves. For example, if asset 3 lists on market 1, the ability of market makers who trade asset 1 to learn about the private signal $\tilde{s}_1$ increases because they can observe the order flow in asset 3. Therefore, the new listing provides a positive externality to the market. We can further show that when $|a| > |b|$, the improvement to the liquidity of asset 1 when asset 3 lists on market 1 is greater than the improvement to the liquidity of asset 2 when

[10] See also Strobl (2001) who investigates the allocation of multiple stocks to specialists on the NYSE in a noisy rational expectations framework. Bhattacharya, Reny, and Spiegel (1995) look at market breakdowns driven by adverse selection when multiple securities are traded on a single market. They demonstrate the effect of destructive interference that might occur when the payoffs of the traded securities are too highly correlated.

[11] One could claim that this logic should also apply to allocation of stocks to specialists on the floor of the NYSE. In other words, that liquidity would be enhanced if stocks with correlated payoffs are traded by the same specialist. Unfortunately, the limitations of any single person with respect to information processing or interactions with brokers and computer screens prevent specialists from trading stocks that are very similar (like two large technology stocks). The reason is that when there is news about a firm or an industry, the number of orders that arrives for one active stock makes the specialist (and the specialist's clerk) unable to handle trading in any other security. This is because most trades on the NYSE require the specialist (or the clerk) to manually approve the execution. Having another actively traded security that is influenced by the same news event at the same time would prevent the specialist from maintaining an orderly market in either security.

asset 3 lists on market 2 (and vise versa if $|b| > |a|$).[12] This result is rather intuitive because the efficiency with which market makers learn about private information depends on the strength of the commonality in the payoffs of the existing and new assets.

II Empirical Evidence

If managers care about liquidity, Proposition 1 implies that firms would list on markets where similar securities are listed. While the intuition from our model is very general, we carry out empirical tests on the two main U.S. markets: NYSE and Nasdaq.

The sample and data sources are discussed in Section II.1. The tests in Section II.2 have two goals. First, we examine whether the basic assumption of the model—that the two markets differ in terms of the return patterns of the securities listed on them—holds. Second, we study the "passive" decisions of firms that are eligible to move (to the other market) but do not. Our model implies that eligible stocks should not move if their returns are more correlated with securities listed on their own market than with the securities on the other market.

In Section II.3 we present tests of the "active" decisions of managers using a sample of firms that switch markets. Our model predicts that a firm would switch if its return pattern has changed and it resembles more the return patterns of stocks on the other market. We also discuss in this section the robustness of our conclusions to return behavior induced by correlated liquidity trading among stocks that are listed on the same market.

II.1 Sample and Data

We use the CRSP database to generate a universe of all securities that were traded continuously in 2001, our sample period, on either the NYSE or the Nasdaq National Market

[12] To prove this claim we verified that whenever $|a| > |b|$,

$$\frac{(1+|b|)}{2\sqrt{a^2+(1+|b|)^2}} - \frac{(1+|a|)}{2\sqrt{b^2+(1+|a|)^2}} < 0$$

where the first term is the price impact of asset 1 when asset 3 lists on market 1 and the second term is the price impact of asset 2 when asset 3 lists on market 2.

(henceforth Nasdaq or NNM). These criteria result in 5,565 securities, 2,388 from the NYSE and 3,177 from Nasdaq. We then identify on the NYSE common stocks that were eligible to list on Nasdaq on the first day of the year, and similarly Nasdaq stocks that were eligible to list on the NYSE on that date.

Both markets allow for multiple standards of eligibility. For example, one NYSE standard requires a minimum level of earnings in the previous three years while another standard does not set an earnings criterion as long as firms have at least $1 billion in market capitalization and $100 million in revenue. Nasdaq Standard 1 specifies minimum stockholders' equity of $15 million and minimum income of $1 million while Standard 3 does not put forward any demands on either stockholders' equity or income. Instead, firms must meet requirements on market capitalization, assets, or revenue.

While the different standards of the two markets offer flexibility to firms, they do prevent the listing of some securities. Each market has its own philosophy on the firms it wants to attract. While both markets compete fiercely for the large, heavily-traded firms, the more stringent requirements of the NYSE make Nasdaq the only choice for many smaller or younger firms.

In order to investigate the listing choices of managers, we need to identify the firms that actually have a choice: those that are listed on one market and satisfy the listing requirements of the other market. We therefore use information in the CRSP and COMPUSTAT databases to evaluate each stock and see if it satisfies the listing requirement of the other market. Most criteria specified by the NYSE and Nasdaq can be mapped rather well to the information in these two databases. Appendix B contains the variables we use from CRSP and COMPUSTAT for each of the listing requirements. Some slippage, however, is inevitable as the NYSE and Nasdaq evaluate information provided by the firms themselves that is not necessarily identical to what we observe in the databases.[13] Therefore, despite

[13]Probably the most notable difficulty is with public float information, defined as total shares outstanding less any shares held by officers, directors, or beneficial owners of 10 percent or more. No academic database (to our knowledge) contains historical public float data. Our attempts to construct such a variable from information in CRSP and insider filings from Thomson Financial Securities Data proved unsuccessful.

our best efforts, the procedure we use to determine eligibility may introduce some noise into the analysis.

Our procedures identifies 1,055 NYSE common stocks that were eligible to list on Nasdaq on January 1, 2001. We will refer to them throughout the analysis as the NYSE eligible group (or NYSEe). The remaining NYSE securities in our universe (1,333) will be referred to as the non-eligible NYSE group (or NYSEne).[14] Similarly, our procedure yields a list of 415 Nasdaq National Market (NNM) common stocks that were eligible to list on the NYSE at the beginning of our sample period, henceforth NNMe. The other Nasdaq securities in our universe (2,762) will be referred to as the Nasdaq non-eligible group (or NNMne).

Table 1 presents summary statistics for the securities using information from the CRSP database. The median market capitalization of non-eligible securities is lower than that of eligible ones. Non-eligible securities in both markets also trade less and have lower prices. This pattern, however, does not extend to returns. The median observation of the average daily returns of non-eligible NYSE securities is almost identical to that of eligible NYSE stocks. In addition, while non-eligible Nasdaq securities have greater daily return standard deviations than eligible Nasdaq stocks, the situation is reversed for NYSE securities where the return standard deviation of NYSEne is smaller than that of NYSEe. Firms that are eligible to list on both markets are clearly larger and have a more active investor base, but this does not seem to have any obvious implications for the means and standard deviations of their returns during the sample period. The tests in Section II.2 use CRSP daily returns in 2001 to examine the similarity in return patterns between eligible and non-eligible securities on both markets.

Our tests in Section II.3 use a sample of all common stocks that voluntarily switched between the Nasdaq National Market and the NYSE in 2001.[15] There were 28 firms with

[14]The group of non-eligible securities include non-common stocks (ADRs, REITs, etc.). We include them because market makers in our model can potentially learn useful information from all other securities that are listed on the same market. We see no reason to restrict the market makers' information set in the empirical work. We focus on common stocks for the eligible groups in order to make the determination of eligibility less complex (and therefore to reduce potential misclassifications).

[15]The NYSE revised Rule 500 in 1999 to make it easier for firms to delist. The amended rule no longer

common stocks (CRSP share codes 10 and 11) that switched markets: 27 moving from Nasdaq to the NYSE and one moving in the opposite direction. The only switch from the NYSE to Nasdaq was involuntary: the NYSE notified TD Wood's Corp. that it did not meet the NYSE's continuing listing criteria. Therefore, we are left with 27 voluntary switches. Panel A of Table 2 lists the 27 firms in the sample and the dates of their moves, while Panel B provides summary statistics on the switching sample.

II.2 Similarity in Return Patterns: NYSE and Nasdaq Stocks

In this section we look at the return patterns of NYSE and Nasdaq firms. First, we would like to see if the assumption of our model that the two markets differ in terms of the return patterns of the firms that are listed on them indeed holds. We also would like to investigate here the "passive" decisions of firms to stay on a given market. If indeed these are optimal in the sense of our model (i.e., they maximize liquidity), it must be that stocks that are eligible to move to the other market but stay are more similar to securities listed on their market than to securities listed on the other market.

When we move from the theoretical model to the empirical tests, we need to define what we mean by "similar" firms. In the model, similarity was formalized by a common source of variation in the payoffs. In the empirical work, we would like to capture this similarity by looking at the daily return patterns of firms. Still, there is more than one way in which the model can be used to motivate empirical definitions of such similarity, and we are using two separate definitions in our tests.

For the first definition of return similarity we interpret the private information in the model as information about common factors in returns. "Pure" Nasdaq stocks may be more sensitive to a certain common factor, say s_1, while "pure" NYSE stocks may be more sensitive to another common factor, s_2. According to this interpretation, θ_1, θ_2, and θ_3 represent unsystematic risk and are therefore uncorrelated with each other. Our model

required shareholders' approval (just that of the board of directors). One firm voluntarily switched from the NYSE to Nasdaq in 2000 (see Kalay and Portniaguina (2001)), but none did so in 2001.

predicts that Nasdaq stocks that are eligible to list on the NYSE would stay on Nasdaq if they are more sensitive to s_1 than to s_2, or that $|a| > |b|$ (see Proposition 1). Similarly, NYSE stocks that are eligible to list on Nasdaq remain on the NYSE because their returns are more sensitive to s_2, like the other NYSE securities, than to s_1.

Our second definition of return similarity interprets a private signal in the model as information that can be relevant to certain firms but not necessarily to the entire market. Since θ_i in our model could be correlated across securities, it can be thought of as a stock specific sensitivity to the market portfolio multiplied by the excess return on the market. Therefore, θ_i assumes the role of the common element in returns, while the independent signals, s_1 and s_2, induce some comovement in the returns of certain stocks even if they are not common to the entire economy.[16] Under this interpretation, we would obtain a cleaner picture of return variation due to the private signals by removing the influence of the market portfolio and looking at return residuals.

The methodology we use to examine the first definition of return similarity is principal component analysis, where we look at the sensitivities of NYSE and Nasdaq stocks' returns to common sources of return variation. Because there are 248 days in the sample period and 5,565 securities, we form 15 portfolios from the securities in each group (for a total of 60 portfolios).[17] Since each group contains a different number of securities, N, we randomly assign approximately $N/15$ securities to each portfolio. For example, the 1,055 stocks in the NYSEe group are divided such that 14 portfolios contain 70 stocks each, and one portfolio contains the remaining 75 stocks. Portfolio returns are computed as averages of the daily returns on the stocks in the portfolio. We then perform a principal component analysis of daily portfolio returns in 2001.[18] To be consistent with the model, we retain the first two

[16] This does not change if one adds uncorrelated sources of noise, ϵ_1 and ϵ_2, to the payoffs of securities 1 and 2, respectively.

[17] We aggregate securities into portfolios because the principal component analysis cannot identify loadings when the number of observations (days) is smaller than the number of variables (securities).

[18] We repeated the analysis with equal number of securities in each of the 60 portfolios by randomly drawing without replacement 25 securities from each group to form each portfolio. The number of stocks was chosen such that even the smallest group (NNMe) would enable us to form 15 different portfolios with 25 stocks each. The results of this analysis were similar to the results presented below and are therefore not reported.

principal components and use an orthogonal rotation.[19] The procedure provides estimates of the loadings on the two principal components. These loadings can be interpreted as the bivariate correlations between the portfolios' returns and the principal components.

Panel A of Table 3 shows the mean and standard deviation of the rotated factor loadings of the four groups of securities. The mean loading on the first component of eligible Nasdaq stocks is 0.813, much closer to the mean of non-eligible Nasdaq securities, 0.795, than to that of either NYSE groups, 0.437 (NYSEne) or 0.488 (NYSEe). Nasdaq securities seem to load more heavily on the first component than do NYSE securities. In Panel B of Table 3 we use an ANOVA to further examine the difference between the loadings of the different groups. The results indicate that the main effect of being listed on a particular market is highly statistically significant (p-value< 0.0001). The difference in the means of the loadings on the first principal component between Nasdaq and NYSE securities is 0.34 while the difference between the loadings of securities that are eligible to list on the other market and those that are not is only one tenth that magnitude (0.035). Nonetheless, the variability of the estimated loadings is small enough so that the main effect of eligibility is statistically significant as well (p-value$= 0.0037$).

While Nasdaq securities load more heavily on the first principal component, NYSE securities load more heavily on the second component. The mean loading of NYSE eligible portfolios is 0.799, much closer to the magnitude of the other NYSE securities (0.798) than to the mean loading of either Nasdaq groups: 0.493 (NNMne) or 0.429 (NNMe). The ANOVA also recognizes significant market and eligibility effects for the second principal component (and a significant interaction as well).[20] As before, the market effect is more significant and the difference in the means between Nasdaq and NYSE securities is more than ten times greater than the difference in the means between the loadings of eligible and non-eligible securities.

[19] We apply the commonly used VARIMAX rotation. See, for example, Kaiser (1958) and Hatcher (1994).

[20] An ANOVA simple effects analysis shows that there is no significant difference between the NYSEe and NYSEne estimates (0.799 and 0.798). The significant interaction is driven by differences between the Nasdaq groups (0.493 and 0.429).

The results of the principal component analysis are important in two respects. First, if we take the principal components to represent estimates of common factors, Nasdaq stocks are more sensitive to one factor (s_1) and NYSE stocks are more sensitive to another factor (s_2). This finding is consistent with the assumption that we use as the primitive of our approach: that there are two groups of firms with different return patterns and each group is listed on a different market. Evidence consistent with the basic setup of the model increases our confidence in the implications of the model. Second, since our test separates eligible and non-eligible stocks in each market, we are able to look at the "passive" optimality of firms' decision to stay on a market (as opposed to the "active" optimality of switching firms that we investigate in the next section). We find that eligible stocks in each market have loadings that are more similar to those of non-eligible securities in the same market than to loadings of securities listed on the other market. This evidence is consistent with the eligible firms' managers making optimal (passive) listing decisions by not moving to the other market.

We also conduct a test of the "passive" optimality of firms' decisions using the second definition of similarity in return patterns that we discussed at the beginning of this section. To remove the effect of common variability in returns and focus on the private signals, we run a market model for each security using daily returns in 2001 and the Standard and Poor's 500 Index as a proxy for the market portfolio. We then take the residuals from the market model and normalize them to have unit variance.

Note that in the model, the comovement of the payoffs of asset 1 and asset 3 in market 1 after eliminating θ_1 and θ_3 is simply a. Similarly, the comovement of asset 2 and asset 3 in market 2 after eliminating θ_2 and θ_3 is equal to b. Proposition 1 states that the difference between the absolute values of a and b determines the optimal choice of a manager between the two markets. Our market model procedure is meant to eliminate θ_{i} from the returns of all securities. Therefore, to estimate $|a|$, we compute for each eligible stock the correlation between its normalized residual and the normalized residuals of all non-eligible securities on Nasdaq. We denote the average of the absolute values of these correlations as $|\bar{a}_{\mathsf{i}}|$. To estimate b, we compute for each eligible stock the correlation between its normalized residual and the normalized residuals of all non-eligible securities on the NYSE. We denote the average of the absolute values of these correlations as $|\bar{b}_{\mathsf{i}}|$.

If eligible Nasdaq securities optimally stay on Nasdaq, it should be that the average absolute value of their correlations with non-eligible Nasdaq securities is greater than the average absolute value of their correlations with non-eligible NYSE securities. Similarly, for eligible NYSE stocks we would predict that their estimates of $|\bar{b}_{\mathsf{i}}|$ (the magnitude of comovement with non-eligible NYSE securities) will be greater than their estimates of $|\bar{a}_{\mathsf{i}}|$ (the magnitude of comovement with non-eligible Nasdaq stocks). Therefore, we test whether $|\bar{a}_{\mathsf{i}}| - |\bar{b}_{\mathsf{i}}| > 0$ for NNMe and $|\bar{b}_{\mathsf{i}}| - |\bar{a}_{\mathsf{i}}| > 0$ for NYSEe.

Panel A of Table 4 provides the means and medians of $|\bar{a}_{\mathsf{i}}|$, $|\bar{b}_{\mathsf{i}}|$, and $|\bar{a}_{\mathsf{i}}| - |\bar{b}_{\mathsf{i}}|$ for the 415 eligible Nasdaq stocks. The t-test indicates that the mean of $|\bar{a}_{\mathsf{i}}| - |\bar{b}_{\mathsf{i}}|$ is positive and highly statistically significant (p-value$= 0.0079$). Similarly, a Wilcoxon signed-rank test shows that the median is positive and statistically significant. Panel B of Table 4 provides the results for the 1,055 eligible NYSE stocks. The mean and median of the differences $|\bar{b}_{\mathsf{i}}| - |\bar{a}_{\mathsf{i}}|$ are positive and even greater in magnitude than those of the Nasdaq stocks. Both tests are highly statistically significant (p-value< 0.0001). These findings provide additional support to the hypothesis that managers of firms choose to list their companies on the market where similar firms are listed. We qualify this conclusion at this point because so far we only tested the "passive" choices of managers—where we infer the choice from no action taken to move the stock to a different market. In the next section we examine the "active" choices of managers to switch markets.

II.3 Tests using Switching Firms

In this section we test of the implications of our model using firms that switched from Nasdaq to the NYSE in 2001. Our model posits that a stock's return pattern affects its liquidity via the interaction with other securities that are listed on the same market. If the decision to switch markets is motivated by the desire to improve liquidity, it must be that the return patterns of the stocks that switch had changed to make their old market no longer optimal. We therefore would like to examine changes in the return patterns of stocks that switch prior to their actual move to see if indeed they become more similar to the return patterns of stocks on the new market.

The use of switching firms to test the implications of our model has another advantage in that it helps in distinguishing our mechanism from the alternative hypothesis that the return patterns we documented in Section II.2 are due to correlated liquidity trading. More specifically, say each market has its own class of liquidity (or noise) traders who trade the assets listed on their market but not assets listed on the other market. For example, a class of such informationless traders could be those buying and selling index funds. As some indexes are market specific (e.g., the Nasdaq 100 Index), it is conceivable that cash flows into and out of such index funds or creation and redemption of Exchange Traded Funds that follow market-specific indexes (e.g., the QQQ) may cause the prices of assets listed on the same market to move together.

What happens if we introduce into the model of Section 1 correlated liquidity trading for assets that are listed on the same market? Let ρ denote the correlation among liquidity traders. Figure 1 shows how the value of the difference in equation (3) changes with ρ.[21] To maintain a two dimensional figure, we fix $a = 1$ and draw 5 lines: two for $|a| > |b|$, two for $|a| < |b|$, and one for $|a| = |b|$. We see that the two curves for which $|a| > |b|$ are in the negative domain implying better liquidity on market 1, and the difference $\lambda_3(1)^2 - \lambda_3(2)^2$ becomes more negative as ρ increases. The opposite happens when $|a| < |b|$: the two curves are in the positive domain implying that liquidity is better on market 2, and the difference is monotonically increasing with ρ. Therefore, the main implication of our model (Proposition 1) still holds when correlated liquidity trading is considered.

There are clear distinctions between our model and this alternative hypothesis. The

[21]The solution to the model with correlated liquidity trading is available from the authors upon request.

model uses return patterns as a primitive and suggests that these determine optimal listing choices that reinforce the situation where firms listed on the same market have more similar return patterns. On the other hand, the alternative hypothesis takes the act of listing as a primitive and claims that listing on a market brings about correlated liquidity trading and thus induces similarity in the return patterns of the listing firm and other firms traded on the same market.[22] To examine the robustness of our conclusions to the alternative hypothesis, we would like to see whether changes in return patterns occur before a firm is listed on a market, and whether the listing decision is consistent with moving to a market populated by firms with similar return patterns.

There are a couple of issues that should be mentioned upfront with respect to this exercise. First, there may be other reasons for firms to switch markets (e.g., a preferred regulator). Switches that are motivated by other considerations would introduce noise into the tests and make it more difficult for us to find an effect. Second, there are really no guidelines for how long prior to a switch we should analyze the data to detect the changes in return patterns. It is reasonable to look at the year prior to the move as the decision to move was probably made at that point. But this decision could have been made following a long period in which the return pattern changed to be more like that of firms listed on the other market before managers decided to switch.[23] Therefore, the choice of a period to analyze prior to a switch is arbitrary in nature. With these reservations in mind, we proceed to use the methodologies from Section II.2 to examine the return patterns of the stocks in the switching sample.

Our first test is based on the principal components methodology. As Table 2 shows, the 27 switches occur at different times during the year. Because the principal component analysis requires having the same time interval for all stocks, we use calender time to define the periods we investigate. In other words, we look at the similarity of return patterns in

[22] See also Chan, Hameed, and Lau (2003).

[23] One could also argue that managers may be able to foresee that their firms would become more similar to NYSE firms before the return patterns change, and so the move would come in anticipation of this process. Of course, the implication of this interpretation is similar to that of the alternative hypothesis and so our tests would not be able to separate the two.

calender years 1999 and 2000. Later in this section we implement the methodology using correlations of normalized market model residuals where we are able to study what happens one, two, and three years prior to the switch date defined individually for each stock in the sample.

The first step in the principal component methodology is to generate from the CRSP database a universe of all securities that were traded continuously in 1999 on either the NYSE or the Nasdaq National Market (excluding the 27 stocks in our switching sample). As in Section II.2, we form 30 portfolios from the stocks in each market (for a total of 60 portfolios). Say a market contains N securities; we randomly assign approximately $N/30$ securities to each portfolio. We also form a switching portfolio by computing the equal-weighted returns in 1999 of the stocks that moved from Nasdaq to the NYSE in 2001 (our sample firms). Using these 61 portfolios, we then perform a principal component analysis of daily portfolio returns in 1999 and retain the loadings on the first two principal components.

We want to look at the "distance" of the switching portfolio's loading from the loadings of the NYSE and NNM portfolios, and how this distance changes over time. We therefore compute 30 distances of the switching portfolio loading from NYSE stocks by taking the absolute value of the difference between the loading (say on the first principal component) of the switching portfolio and the loadings on the same principal component of the 30 NYSE portfolios. Similarly, we compute 30 distances of the switching portfolio's loading from the loadings of the NNM portfolios. We repeat this procedure of randomly assigning securities into portfolios and performing a principal component analysis 100 times.

Panel A of Table 5 shows the mean, median, and standard deviation of the distances from the NYSE and NNM stocks across the $3,000$ observations (30 distances from each market times 100 random assignments) for the first principal component. The mean distance of the switching portfolio's loading from the loadings of the NYSE portfolios is 0.3372, and is larger than the mean distance of the switching sample from the NNM portfolios, 0.1157. The statistical tests we perform are all highly significant, indicating that the distance of the switching sample from NYSE stocks is indeed much larger than the distance of the switching sample from NNM stocks.[24] Panel B of Table 5 shows the results for the second principal component. The mean distance of the switching portfolio's loading from the loadings of the NYSE portfolios is 0.2480, and all tests show that it is significantly larger than the mean distance of the switching portfolio from the NNM portfolios, 0.1016. Our sample stocks in 1999 indeed look more like other Nasdaq stocks than like NYSE stocks.

We repeat the same procedure for the year 2000, and the results in Table 5 indicate a pronounced shift. The average distance of the switching sample from NYSE stocks is smaller than its average distance from NNM stocks, and all statistical tests indicate that indeed the NYSE distance is significantly smaller. This is true for both the first and second principal components. It appears that indeed the return patterns of the stocks in the switching sample become more similar to those of NYSE stocks over that time period.[25]

Our next test is based on the second methodology of Section II.2 (the market model residuals). We run for each security a daily market model in each calender year (1998-2001), and save the normalized residuals. We do the same for our sample of switching stocks. Now we define three non-overlapping one-year periods for each stock in the sample relative to the date it moved to the NYSE: from the switch date to one year prior to that date (henceforth period $t-1$), from one year prior to the date to two years prior to the date (period $t-2$), and from two years prior to the date to three years prior to the date (period $t-3$). For each of the one-year periods prior to the switch and for each stock in the switching sample we compute $|\bar{a}_i|$ and $|\bar{b}_i|$ as in Section II.2.[26]

[24] We report several statistical tests of the hypothesis that the distance of the switching sample from NYSE stocks is different from the distance of the switching sample from NNM stocks. First, we perform a t-test and a Wilcoxon signed-rank test using all 3000 observations. Second, we perform a separate test on each random draw (30 observations), average the magnitude of the t-statistic or the Z-statistic over the 100 random draws, and report the p-value associated with this average magnitude. We also report how many of the 100 tests are significant at the 5% level.

[25] Note that we do not need to utilize a separate control sample in order to establish this result because our methodology uses all securities listed on each market as a control, and our tests compare differences between our sample and these controls.

[26] If there are fewer than three months of daily returns common to a sample switching stock and a Nasdaq or NYSE security on any given one-year period, we do not include the correlation between them in the computation of $|\bar{a}_i|$ or $|\bar{b}_i|$.

Table 6 provides the cross-sectional means and medians of $|\bar{b}_i| - |\bar{a}_i|$ for the 27 stocks in our switching sample in each of the one-year periods, as well as p-values from a t-test and a Wilcoxon signed-rank test against the hypothesis of a zero difference. In period $t-3$, the mean magnitude of the difference is 0.0016, but none of the tests is statistically significant indicating that the correlation measures of the switching stocks with stocks listed on both markets are similar in magnitude. The mean difference increases to 0.0035 in period $t-2$ and then again to 0.0048 in period $t-1$ (the year prior to the switch). The statistical tests are highly significant in both those periods, indicating that the return patterns of the switching stocks are moving in the direction of being more similar to those of NYSE stocks.

To summarize, both methodologies provide evidence that the return patterns of stocks that switch from Nasdaq to the NYSE become more similar to the return patterns of stocks listed on the NYSE and less similar to the return patterns of Nasdaq stocks prior to switching. In fact, this change is documented up to two years before moving to the NYSE and hence is likely to have been underway when the decision to switch was made. These findings have two implications for our discussion. First, they document a change in return patterns prior to a decision to switch listings, which is consistent with our model where return patterns affect the listing decision. Second, they show a shift to having return patterns more similar to NYSE stocks prior to the sample stocks actually moving to list on the NYSE. This supports the conclusion that managers behave in accordance with our model, or that they switch markets to maximize the liquidity of their stocks. The results of this section are therefore consistent with our findings in Section II.2 that managers of firms optimally choose to list their companies on the market where similar firms are listed.

III Conclusion

In this paper we provide an explanation for the listing choice of firms based on asset returns. To make this point very clear, our model features two markets with the same structure and price setting rules. As a primitive of the problem we assume that securities listed on the two markets differ with respect to their return patterns. There are many ways in which such a situation can arise. For example, it may be caused by listing requirements: one market sets listing requirements that are met only by very large firms, while another market tries to attract small start-ups. Examples of markets that cater to different firms exist around the world and reflect a multitude of business models and marketing decisions. The end result is that more related firms tend to be traded on the same market.

Our approach does not state that listing requirements and other market-specific elements have no role in determining the listing choice. What it does, however, is to identify a specific mechanism that creates an optimal listing choice when stocks with different return patterns are listed on different markets. The mechanism we propose is that information asymmetry among investors creates differences in liquidity depending on the market on which a firm chooses to list. In fact, that mechanism will tend to perpetuate itself (firms will continue to list on the market where similar firms are listed) and therefore can create path-dependence even if the reason for the initial clustering of similar firms on a market no longer exists.

Our model suggests that by making optimal listing decisions, managers can help reduce the adverse selection costs incurred by investors who trade their firms' stocks. Indeed, managers often cite liquidity as a factor in choosing a market.[27] Firms listed on the Deutsche Börse even pay Designated Sponsors to act as market makers for the firms' stocks in order to enhance their liquidity. A primary reason for managers to care about liquidity is if they maximize shareholder wealth and liquidity is priced, with the latter currently being the subject of intense research in asset pricing and market microstructure. However, even if liquidity is not priced directly (i.e., it does not affect the firm's cost of capital), there may be other reasons for a manager to care about liquidity. For example, liquid stocks may attract a larger investor base, which would make it easier for the firm to issue more equity and negotiate with underwriters for a lower fee. Irrespective of the specific rationale that makes managers care about liquidity, our empirical results suggest they do.

[27] See, for example, the surveys by Baker and Pettit (1982), Freedman and Rosenbaum (1987), and Baker and Johnson (1990).

We test our model on the two dominant markets in the U.S.: NYSE and Nasdaq. We first consider if indeed the basic assumption of our model—that there are two groups of firms with different return patterns each listed on a different market—holds for the NYSE and Nasdaq. We show that Nasdaq securities load more heavily on one principal component of returns while NYSE securities load more heavily on another principal component, consistent with the assumption of the model. We also show that the loadings of Nasdaq stocks that are eligible to list on the NYSE look more similar to those of non-eligible Nasdaq securities than to those of NYSE securities; NYSE stocks that are eligible to list on Nasdaq look more like non-eligible NYSE securities than Nasdaq securities. We then use correlations of market model residuals to define similarity of return patterns and find that the return residuals of eligible stocks comove more with the return residuals of non-eligible securities from their own market than with the return residuals of securities from the other market.[28] The results of these tests suggest that the passive choice made by managers of the eligible firms not to switch markets is optimal. By that we mean that the return patterns of eligible stocks that remain listed on their market despite the ability to switch are such that staying is indeed the liquidity maximizing thing to do.

We then turn to tests of managers' "active" choices by looking at firms that switch markets. These tests have the advantage that they separate our approach from an alternative hypothesis according to which correlated liquidity trading may induce comovement in the returns of firms that are listed on the same market. We find that the return patterns of stocks in the sample change before the actual change in listings (and possibly before the decision on the change in listings was made), and that the change makes them more similar to stocks listed on the new market. These results are consistent both with our model, where return patterns affect listing decisions, and with our conclusions that managers act to maximize liquidity by their choice of where to list their stocks.

[28]It is, of course, possible that the true return generating process has a multi-factor structure and the residuals from the market model contain some systematic elements. This does not change our conclusions because our theoretical model would imply a similar test in this case, and therefore the results we find would suggest optimal listing decisions under this alternative interpretation as well.

Our model also implies that a new listing generates a positive externality for the firms already listed on a market: the liquidity of the existing asset improves when the new asset lists because market makers can learn private information on the signal that is common to both assets. Managers who decide on the listing venue for their firms may not take that effect into account when making their choices. Hence, deciding on a listing venue using a different criterion (not liquidity maximization) could be socially suboptimal in that it may prevent the improvement in liquidity that the other stocks would experience if the decision was made on the basis of return patterns. Already listed firms may therefore have an incentive to lure new firms that they consider "similar" to enjoy the positive externality.

Our work demonstrates how corporate decision making can be shaped by patterns of asset returns beyond, for example, the exercise of figuring out the hurdle rates for projects. The connection we form between asset pricing and corporate finance goes through market microstructure and shows how the investigation of imperfections in the trading environment of assets may hold some clues to the relation between asset returns and decision making within the firm.

Appendix A

Proof of Theorem 1: Without loss of generality, assume that the value of the assets prior to the innovation is zero ($\mu = 0$). Conjecture that the price rule is linear. Then, the i-th informed trader problem is

$$\max_{X_i \in R^2} E[(V - \Lambda Y)X_i | s_i].$$

Because (i) $cov(s_1, s_2) = 0$, (ii) s has zero mean, and (iii) the other informed trader follows a linear strategy, we have

$$E[(V - \Lambda Y)X_i | s_i] = E[(E[V|s_i] - \Lambda X_i)X_i | s_i].$$

The first order condition implies

$$X_i = (\Lambda + \Lambda^\top)^{-1} E[\tilde{V}|s_i].$$

Thus, the strategy of the i-th trader is also linear. Also

$$X = X_1 + X_2 = (\Lambda + \Lambda^\top)^{-1} E[\tilde{V}|s_1] + (\Lambda + \Lambda^\top)^{-1} E[\tilde{V}|s_2] = (\Lambda + \Lambda^\top)^{-1} FS.$$

We therefore have $\beta = (\Lambda + \Lambda^\top)^{-1} F$ in the first equation of (2). From the theory of linear filtering (see, for example, Bensoussan, 1992, Theorem 1.1.1) it follows that the matrix Λ is given by the second equation in (2).

To solve the system, we guess (and verify later) that Λ is symmetric. From the first equation in (2), we have

$$\beta = 0.5\Lambda^{-1} F. \tag{4}$$

Multiply the second equation from the left by Λ^{-1}, and insert β to get

$$I = 2\beta\beta^\top (I + \beta\beta^\top)^{-1}$$

Multiply both sides from the right by $(I + \beta\beta^\top)$ to get

$$I + \beta\beta^\top = 2\beta\beta^\top$$

Subtract $\beta\beta^\top$ from both sides

$$I = \beta\beta^\top.$$

Insert the above in (4) to get

$$\frac{1}{4} F F^\top = \Lambda\Lambda. \tag{5}$$

The matrix equation in (5) has more than one solution. The linear equilibrium is the one in which $-\Lambda$ is negative semi-definite. This solution is given below.[29]

$$\Lambda = \begin{pmatrix} \frac{(1+|b|)}{2\sqrt{a^2+(1+|b|)^2}} & \frac{a}{2\sqrt{a^2+(1+|b|)^2}} \\ \frac{a}{2\sqrt{a^2+(1+|b|)^2}} & \frac{a^2+|b|(1+|b|)}{2\sqrt{a^2+(1+|b|)^2}} \end{pmatrix} \tag{6}$$

[29] In particular, we verify that Λ is indeed symmetric, and that Λ is positive semi-definite: $\Lambda_{11} > 0, \Lambda_{22} > 0$ and $\Lambda_{11}\Lambda_{22} - \Lambda_{12}\Lambda_{21} = \frac{1}{4}|b| > 0$.

Appendix B

The listing requirements of both the New York Stock Exchange and Nasdaq National Market can be found on their respective web sites.[30] We use data in CRSP and COMPUSTAT to identify Nasdaq National Market common stocks that were eligible to list on the NYSE and NYSE common stocks that were eligible to list on Nasdaq on January 1, 2001. Below we provide the specific data items from CRSP and COMPUSTAT that we have used for the listing criteria of each market.

Database Definitions for Nasdaq National Market Listing Requirements

- Net Tangible Assets:[31] COMPUSTAT (Data 6 − Data 181 − Data 204)
- Market Capitalization: CRSP (|prc|*curshr, for 90 consecutive days ending December 31, 2000)
- Total Revenue: COMPUSTAT (Data 12)
- Total Assets: COMPUSTAT (Data 6)
- Income from Continuing Operations before Income Taxes: COMPUSTAT (Data 170)
- Public Float (shares): CRSP (curshr, on December 31, 2000)
- Market Value of Public Float: CRSP (|prc|∗curshr, on December 31, 2000)
- Shareholders: COMPUSTAT (Data 100)
- Minimum Bid Price: CRSP (|prc|, for 90 consecutive days ending December 31, 2000)

Database Definitions for New York Stock Exchange Listing Requirements

- Shareholders: COMPUSTAT (Data 100)
- Average Monthly Trading Volume: CRSP (vol, average for the 12 months in 2000)
- Public Shares: CRSP (curshr, on December 31, 2000)
- Market Value of Public Shares: CRSP (|prc|∗curshr, on December 31, 2000)
- Pretax Earnings: COMPUSTAT (Data 170 − Data 49 + Data 55)
- Market Capitalization: CRSP (|prc|∗curshr, for the 12 months in 2000)
- Total Revenue: COMPUSTAT (Data 12)
- Operating Cash Flow: COMPUSTAT (Data 308 − Data 307 − Data 304 − Data 303 − Data 302)

[30] For Nasdaq see http://www.nasdaq.com/about/nasdaq_listing_req_fees.pdf, and for NYSE see http://www.nyse.com/listed/p1020656067970.html?displayPage=%2Flisted%2F1022221392369.html.

[31] On June 29, 2001, Nasdaq replaced the Net Tangible Assets requirement with a Stockholders' Equity requirement.

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Table 1
Summary Statistics: Eligible and Non-Eligible Securities

This table presents the sample of securities that we use for the analysis in Tables 3 and 4. The universe includes all NYSE and Nasdaq National Market securities that were traded continuously in 2001 with information in the CRSP database (5,565 securities). We divide the universe into four groups: (i) NNMe are Nasdaq National Market common stocks that were eligible to list on the NYSE on the first day of the year (415 securities), (ii) NNMne are all other Nasdaq National Market securities in our universe (2,762 securities), (iii) NYSEe are NYSE common stocks that were eligible to list on Nasdaq on January 1, 2001 (1,055 securities), and (iv) NYSEne are all other NYSE securities in our universe (1,333 securities). The following variables are calculated for each security in the 248-day sample period (January-December, 2001) using data in CRSP: AvgCap is the average daily market capitalization (the number of shares outstanding multiplied by the daily closing price), AvgPrc is the average daily closing price, AvgTurn in the average daily turnover (the number of shares traded divided by the number of shares outstanding), AvgVol is the average daily dollar volume, AvgRet is the average daily returns computed from closing prices, and StdRet is the standard deviation of daily returns. The table presents summary statistics for the entire sample and separately for each of the four groups.

		AvgCap (in million $)	**AvgPrc** (in $)	**AvgTurn** (in %)	**AvgVol** (in $1000)	**AvgRet** (in %)	**StdRet** (in %)
Entire	Mean	2489.2	30.94	0.594	15792.2	0.099	4.20
Sample	Median	234.1	13.52	0.338	746.2	0.077	3.55
	Std. Dev.	14126.0	922.40	0.938	75808.4	0.233	2.64
	Obs.	5565	5565	5565	5565	5565	5565
NNMne	Mean	306.5	11.73	0.630	4467.7	0.138	5.55
(non-eligible	Median	93.0	8.38	0.332	283.1	0.129	5.20
Nasdaq	Std. Dev.	1,163.2	16.46	1.064	25350.2	0.276	2.72
securities)	Obs.	2762	2762	2762	2762	2762	2762
NNMe	Mean	4851.5	25.54	1.275	72947.8	0.081	4.38
(eligible	Median	861.5	23.98	0.928	7667.0	0.097	3.94
Nasdaq	Std. Dev.	21844.8	14.74	1.236	219757.5	0.198	1.98
securities)	Obs.	415	415	415	415	415	415
NYSEne	Mean	1394.7	20.85	0.392	6256.8	0.062	2.53
(non-eligible	Median	253.1	13.88	0.235	522.7	0.046	2.13
NYSE	Std. Dev.	5261.9	70.38	0.746	26693.4	0.183	1.80
securities)	Obs.	1333	1333	1333	1333	1333	1333
NYSEe	Mean	8657.5	96.11	0.489	35004.9	0.048	2.69
(eligible	Median	1489.3	26.67	0.397	7200.7	0.047	2.46
NYSE	Std. Dev.	27805.1	2116.37	0.365	81718.0	0.141	1.11
securities)	Obs.	1055	1055	1055	1055	1055	1055

Table 2
Switching Sample

This table presents the sample of switching firms that we use for the analysis in Tables 5 and 6. The sample includes all firms with common stocks that voluntarily switched between the Nasdaq National Market and the NYSE in 2001. Panel A lists the 27 stocks in the sample and the dates they moved from Nasdaq to the NYSE. Panel B provides summary statistics on the switching sample. The following variables are calculated for each stock using 2001 data in CRSP: AvgCap is the average daily market capitalization (the number of shares outstanding multiplied by the daily closing price), AvgPrc is the average daily closing price, AvgTurn in the average daily turnover (the number of shares traded divided by the number of shares outstanding), AvgVol is the average daily dollar volume, AvgRet is the average daily returns computed from closing prices, and StdRet is the standard deviation of daily returns.

Panel A: **Sample Stocks**

Name	NYSE Symbol	Nasdaq Symbol	Switching Date
SOVEREIGN BANCORP INC	SOV	SVRN	7/10/2001
B M C SOFTWARE INC	BMC	BMCS	3/13/2001
BERKLEY W R CORP	BER	BKLY	5/9/2001
MICHAELS STORES INC	MIK	MIKE	12/12/2001
NATIONAL COMMERCE FINANCIAL CORP	NCF	NCBC	7/25/2001
UNITRIN INC	UTR	UNIT	5/24/2001
COVENTRY HEALTH CARE INC	CVH	CVTY	5/16/2001
OXFORD HEALTH PLANS INC	OHP	OXHP	4/18/2001
SYBASE INC	SY	SYBS	5/22/2001
SUPERIOR ENERGY SERVICES INC	SPN	SESI	5/15/2001
CHICOS FAS INC	CHS	CHCS	4/11/2001
MOVADO GROUP INC	MOV	MOVA	5/21/2001
ALLIED CAPITAL CORP NEW	ALD	ALLC	6/6/2001
RENAL CARE GROUP INC	RCI	RCGI	11/13/2001
I D T CORP	IDT	IDTC	2/26/2001
P F F BANCORP INC	PFB	PFFB	12/28/2001
SUNRISE ASSISTED LIVING INC	SRZ	SNRZ	5/23/2001
E TRADE GROUP INC	ET	EGRP	2/15/2001
FLAGSTAR BANCORP INC	FBC	FLGS	7/13/2001
MAXTOR CORP	MXO	MXTR	4/30/2001
CROWN CASTLE INTERNATIONAL CORP	CCI	TWRS	4/25/2001
TRIAD HOSPITALS INC	TRI	TRIH	4/30/2001
TRITON P C S HOLDINGS INC	TPC	TPCS	7/31/2001
ALAMOSA HOLDINGS INC	APS	APCS	12/6/2001
KRISPY KREME DOUGHNUTS INC	KKD	KREM	5/17/2001
IRWIN FINANCIAL CORP	IFC	IRWN	9/21/2001
W HOLDING CO INC	WHI	WBPR	12/5/2001

Panel B: **Switching Sample Summary Statistics**

	AvgCap (in million $)	**AvgPrc** (in $)	**AvgTurn** (in %)	**AvgVol** (in $1000)	**AvgRet** (in %)	**StdRet** (in %)
Mean	1664.7	23.41	0.787	13726.8	0.131	3.52
Median	1318.4	22.73	0.610	10210.0	0.133	3.28
Std. Dev.	1320.2	10.86	0.606	15720.4	0.170	1.10
Obs.	27	27	27	27	27	27

Table 3
Principal Component Analysis

This table presents the principal component analysis of daily returns in 2001. We divide the universe of 5,565 securities into four groups: (i) NNMe are Nasdaq National Market common stocks that were eligible to list on the NYSE on the first day of the year (415 securities), (ii) NNMne are all other Nasdaq National Market securities in our universe (2,762 securities), (iii) NYSEe are NYSE common stocks that were eligible to list on Nasdaq on January 1, 2001 (1,055 securities), and (iv) NYSEne are all other NYSE securities in our universe (1,333 securities). In order to carry out the principal component analysis with 248 daily return observations, we construct 15 equally-weighted portfolios from each group (for a total of 60 portfolios). Let *N* be the number of securities in a group. Each portfolio contains *N*/15 securities. We retain the first two principal components of portfolio returns and use the orthogonal VARIMAX rotation to compute the loadings on the principal components. Panel A presents the means and the standard deviations of the estimated portfolio loadings for the four groups. Panel B presents the *p*-values associated with an ANOVA analysis of the portfolio loadings. The ANOVA main effects are: (i) belonging to a market (NYSE versus Nasdaq), and (ii) eligibility to list on the other exchange (eligible versus non-eligible). The *p*-values are against a two-sided alternative.

Panel A: **Loadings on Principal Components**

Dependent Variable	**1st Principal Component**		**2nd Principal Component**	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
NNMne	0.795	0.027	0.493	0.031
NNMe	0.813	0.033	0.429	0.047
NYSEne	0.437	0.056	0.798	0.032
NYSEe	0.488	0.054	0.799	0.033

Panel B: **ANOVA Analysis of Loadings**

	1st Principal Component	**2nd Principal Component**
	***p*-value**	***p*-value**
Market	<0.0001	<0.0001
Eligibility	0.0037	0.0016
Market*Eligibility	0.1488	0.0010

Table 4
Correlation Analysis of Market Model Residuals

This table presents the analysis of correlation measures estimated from market model residuals. We divide the universe of 5,565 securities into four groups: (i) NNMe are Nasdaq National Market common stocks that were eligible to list on the NYSE on January 1, 2001 (415 securities), (ii) NNMne are all other Nasdaq National Market securities in our universe (2,762 securities), (iii) NYSEe are NYSE common stocks that were eligible to list on Nasdaq on January 1, 2001 (1,055 securities), and (iv) NYSEne are all other NYSE securities in our universe (1,333 securities). We run a market model for each security using daily returns in 2001 and the Standard and Poor's 500 Index as a proxy for the market portfolio. We then take the residuals from the market models of all securities, normalize them to have unit variance, and compute for each eligible stock the correlation between its normalized residual and the normalized residuals of all Nasdaq non-eligible securities. We denote the average of the absolute value of these correlations as $|\bar{a}_i|$. We also compute for each eligible stock the correlation between its normalized residual and the normalized residuals of all non-eligible NYSE securities. We denote the average of the absolute value of these correlations as $|\bar{b}_i|$. Panel A presents the means and medians of $|\bar{a}_i|$, $|\bar{b}_i|$, and $|\bar{a}_i|-|\bar{b}_i|$ for eligible Nasdaq stocks (NNMe group). The last column shows the *p*-values (against a two-sided alternative) of a t-test and a Wilcoxon signed-rank test for zero mean and median differences ($|\bar{a}_i|-|\bar{b}_i|$). Panel B presents the means and medians of $|\bar{a}_i|$, $|\bar{b}_i|$, and the difference between them for eligible NYSE stocks (NYSEe group). The last column shows the *p*-values (against a two-sided alternative) of a t-test and a Wilcoxon signed-rank test for zero mean and median differences ($|\bar{b}_i|-|\bar{a}_i|$).

Panel A: **Eligible Nasdaq Stocks (NNMe)**

	$\lvert\bar{a}_i\rvert$	$\lvert\bar{b}_i\rvert$	$\lvert\bar{a}_i\rvert - \lvert\bar{b}_i\rvert$	***p*-value**
Mean	0.0634	0.0623	0.0010	0.0079
Median	0.0616	0.0610	0.0011	0.0009

Panel B: **Eligible NYSE Stocks (NYSEe)**

	$\lvert\bar{a}_i\rvert$	$\lvert\bar{b}_i\rvert$	$\lvert\bar{b}_i\rvert - \lvert\bar{a}_i\rvert$	***p*-value**
Mean	0.0605	0.0666	0.0060	<0.0001
Median	0.0593	0.0649	0.0046	<0.0001

Table 5

Switching Sample: Principal Component Analysis

This table presents the principal component analysis of the switching sample. We use CRSP to obtain two universes: (i) all securities traded continuously in 1999 on the NYSE and the Nasdaq National Market (NNM), and (ii) all securities traded continuously in 2000 on the NYSE and NNM. The 27-stock switching sample includes all firms with common stocks that voluntarily switched between the NNM and the NYSE in 2001. For each of the years (1999 and 2000) we perform the following steps. We construct 30 random portfolios from each market. Let *N* be the number of securities in a market. Each portfolio contains *N*/30 securities. We carry out a principal component analysis of 61 portfolios (30 from each market and one for the switching sample). We retain the first two principal components of portfolio returns and use the orthogonal VARIMAX rotation to compute the loadings on the principal components. We compute 30 distances of the switching portfolio loading from NYSE (NNM) stocks by taking the absolute value of the difference between the loading of the switching portfolio and the loadings on the same principal component of the 30 NYSE (NNM) portfolios. We repeat 100 times this procedure of randomly assigning securities into portfolios and performing the principal component analysis. Panel A presents the mean, median, and standard deviation of the switching sample's distances from the NYSE and NNM securities across the 3,000 observations (30 distances for each market times 100 random assignments) for the first principal component. We report several statistical tests of the hypothesis that the distance of the switching sample from NYSE stocks is different from the distance of the switching sample from NNM stocks. The first set of t-test and Wilcoxon signed-rank test uses all 3,000 observations. The second set is performed separately on each random draw (30 observations), and we average the magnitude of the t-statistic or the Z-statistic over the 100 random draws and report the *p*-value associated with this average magnitude. The *p*-values are against a two-sided alternative. We also report how many of the 100 tests are significant at the 5% level. Panel B presents the results for the second principal component.

Panel A: **Analysis of Loadings on 1st Principal Component**

	Year 1999		**Year 2000**	
Distances	**|NYSE-Switching|**	**|NNM-Switching|**	**|NYSE-Switching|**	**|NNM-Switching|**
Mean	0.3372	0.1157	0.1932	0.3051
Median	0.3414	0.1143	0.1917	0.3064
Standard Deviation	0.0354	0.0478	0.0669	0.0157
p-value of t-test (3000 Obs.)	<0.0001		<0.0001	
p-value of W-test (3000 Obs.)	<0.0001		0.0000	
Avg. of 100 t-stat. (30 Obs.)	20.29		-8.97	
p-value of average t-stat.	<0.0001		<0.0001	
# of significant tests (5%)	100		100	
Avg. of 100 W-stat. (30 Obs.)	6.63		-5.90	
p-value of average W-stat.	<0.0001		<0.0001	
# of significant tests (5%)	100		100	

Panel B: **Analysis of Loadings on 2nd Principal Component**

Distances	**Year 1999**		**Year 2000**	
	|NYSE-Switching|	**|NNM-Switching|**	**|NYSE-Switching|**	**|NNM-Switching|**
Mean	0.2480	0.1016	0.1836	0.2703
Median	0.2477	0.1045	0.1868	0.2710
Standard Deviation	0.0445	0.0375	0.0359	0.0275
p-value of t-test (3000 Obs.)	<0.0001		<0.0001	
p-value of W-test (3000 Obs.)	<0.0001		<0.0001	
Avg. of 100 t-stat. (30 Obs.)	13.72		-10.50	
p-value of average t-stat.	<0.0001		<0.0001	
# of significant tests (5%)	100		100	
Avg. of 100 W-stat. (30 Obs.)	6.59		-6.36	
p-value of average W-stat.	<0.0001		<0.0001	
# of significant tests (5%)	100		100	

Table 6
Switching Sample: Correlation Analysis of Market Model Residuals

This table presents the analysis of correlation measures estimated from market model residuals for the switching sample. The 27-stock switching sample includes all firms with common stocks that voluntarily switched between the NNM and the NYSE in 2001. We use CRSP to identify all securities traded in the years 1998–2001on the NYSE and the Nasdaq National Market (NNM). We run for each security a daily market model in each calendar year, and normalize the residuals to have unit variance. We define three non-overlapping one-year periods for each stock in the switching sample relative to the date it moved to the NYSE: from the switch date to one year prior to that date (period t–1), from one year prior to the date to two years prior to the date (period t–2), and from two years prior to the date to three years prior to the date (period t–3). For each of the one-year periods prior to the switch and for each stock in the switching sample we compute the correlation between the stock's normalized residual and the normalized residuals of all Nasdaq securities. We denote the average of the absolute value of these correlations as $|\bar{a}_i|$. We also compute for each stock in the switching sample in each one-year period the correlation between its normalized residual and the normalized residuals of all NYSE securities. We denote the average of the absolute value of these correlations as $|\bar{b}_i|$. We present the mean and median of $|\bar{b}_i|-|\bar{a}_i|$ for the 27 stocks in our switching sample in each of the one-year periods, as well as *p*-values from a t-test and a Wilcoxon singed-rank test again the two-sided hypothesis of a zero difference.

	Period t–3	**Period t–2**	**Period t–1**
Mean	0.0016	0.0035	0.0048
Median	0.0006	0.0019	0.0036
***p*-value (t-test)**	0.1200	0.0050	0.0010
***p*-value (Wilcoxon test)**	0.3260	0.0050	0.0020

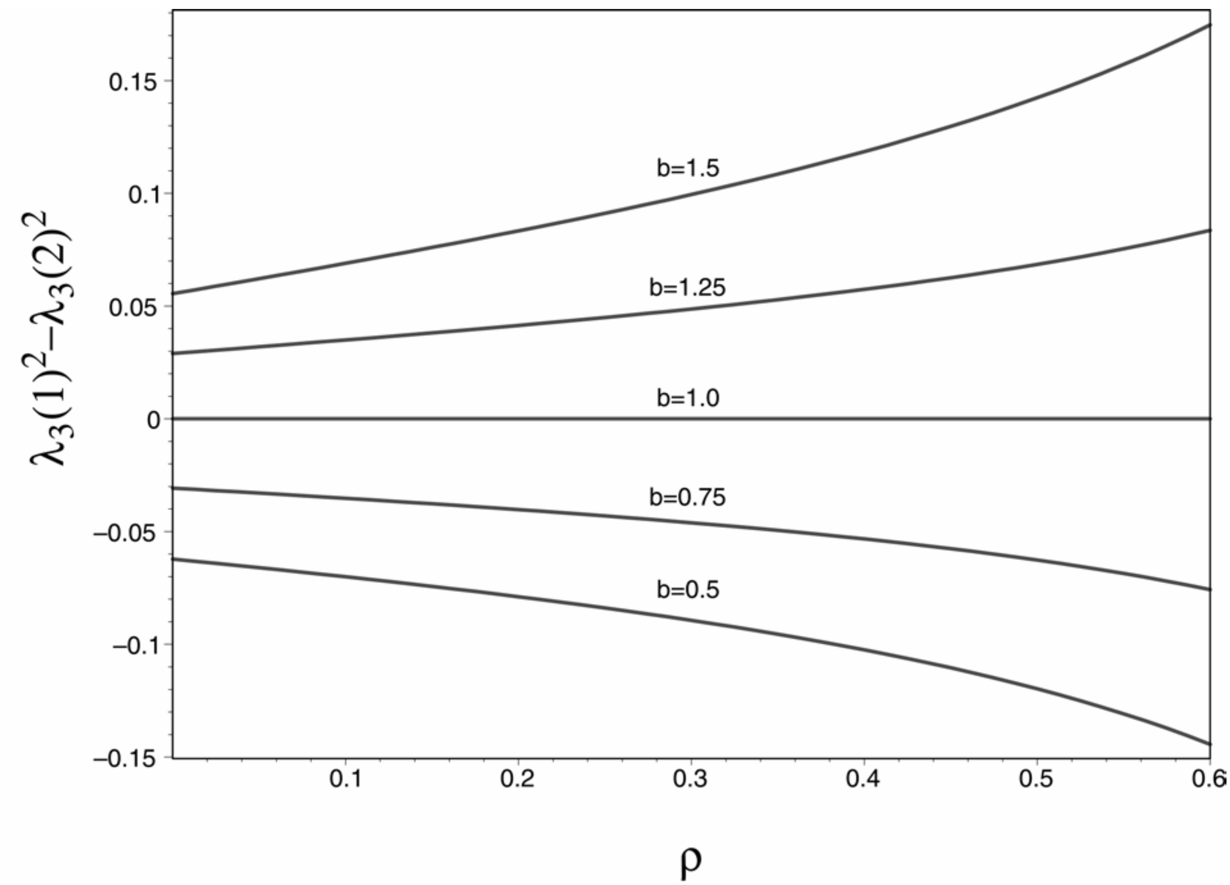

Figure 1

Differences across Markets in Price Impact of Asset 3 with Correlated Liquidity Trading

This figure presents the difference between the squared price impact of Asset 3 when it is listed on Market 1, $\lambda_3(1)^2$, and the squared price impact of Asset 3 when it is listed on Market 2, $\lambda_3(1)^2$, as a function of the correlation in the liquidity demand of the two assets in a market, ρ. When this difference is negative (positive), liquidity is better on Market 1 (Market 2). We fix the value of the sensitivity of Asset 3 to s_1 (a=1), and graph the difference in price impacts as a function of ρ for 5 values of the sensitivity of Asset 3 to s_2: b=0.5, 0.75, 1.0, 1.25, and 1.5.